Feasibility of Unified Analysis Methods for Rotary Screw Trap Data in the California Central Valley.

Task B Report

USFWS Coop Agreement #81420-8-J163

Trent McDonald, Ph.D.
Western EcoSystems Technology, Inc.
2003 Central Avenue
Cheyenne, Wyoming 82001

and

Mike Banach
Pacific States Marine Fisheries Commission
205 SE Spokane Street
Portland, OR 97206

2010-1-22

Funded by the U.S. Fish and Wildlife Service's
Comprehensive Assessment and Monitoring Program (CAMP)
USFWS Cooperative Agreement No. 81420-8-J163

TABLE OF CONTENTS

Introduction

The U.S. Fish and Wildlife Service's Comprehensive Assessment and Monitoring Program (CAMP) produces a variety of reports that summarize and tabulate salmonid data from collection sources in California's Central Valley. To prepare certain of these reports, in-depth statistical analyses and the development of complex databases are required. Through a cooperative agreement, CAMP contracted the Pacific States Marine Fisheries Commission (PSMFC) and a statistical subcontractor (Western EcoSystems Technology; WEST, Inc.) to assist in evaluating the feasibility of developing a comprehensive data collection, storage, and analysis system for information collected from rotary screw traps in the Central Valley. The ultimate purpose of such a system would be to document and understand changes in the abundance of juvenile salmon in the Central Valley. This feasibility study represents Phase 1 of a planned three phase program which may ultimately result in timely and defensible valley-wide estimates of juvenile salmon abundance.

The abundance of juvenile Chinook salmon (*Oncorhynchus tshawytscha*) has been monitored at 12 or more sites in the Central Valley using rotary screw traps (RSTs) for approximately 13 years. Trapping activities at most RST sites has routinely occurred during all or a part of the year since 1995. Much of the collected data have never been presented in report form, and different analytical techniques have been used to estimate fish numbers passing the traps. Separate or non-existent reports and different analytical techniques make it difficult, if not impossible, to understand valley-wide long-term trends in juvenile salmon production. These factors also confound the ability to understand how restoration activities influence juvenile and adult salmon production. To address the difficulties inherent in trend detection under the current system a single comprehensive, multi-faceted data acquisition, storage, and analysis system is needed. This system, if built, would be designed to collect and manage screw trap data, as well as produce statistically robust and repeatable estimates of juvenile Chinook abundance based on RST catch data.

Because the development of such a system is inherently challenging, CAMP determined that a feasibility evaluation was the appropriate first step. This Phase 1 - Task B report addresses the feasibility of implementing uniform data analysis methods to estimate abundance of juvenile Chinook salmon across California's Central Valley. This report is part of a larger feasibility report that includes recommendations for a comprehensive data entry and management system. The uniform analysis methods include algorithms for estimating the abundance of different life stages (fry, parr, smolts, and yearlings) and runs (fall, late fall, spring, and winter). These algorithms are designed to be applicable to all Central Valley RST data, thus unifying estimation methods and making comparison among sites easier.

Activities

PSMFC personnel spoke or corresponded with: Ayesha Gray (Cramer Fish Sciences), Connie Shannon (PSMFC / California Department of Fish and Game), Doug Burch (California

Department of Fish and Game programmer), Doug Threloff (USFWS-Sacramento, CAMP program coordinator) , Michelle Workman (formerly with the East Bay Municipal Utility District and now with the U.S. Fish and Wildlife Service (USFWS)), Liz Cook (formerly with California Department of Water Resources). Meetings attended by Doug Threloff, Mike Banach (PSMFC fisheries biologist), Greg Wilke (PSMFC programmer), Trent McDonald (West, Inc. statistician and programmer), Kellie Whitton (USFWS-Red Bluff biologist), Jim Earley (USFWS-Red Bluff biologist), David Colby (USFWS-Red Bluff biologist), Bill Poytress (USFWS-Red Bluff biologist), and Felipe Carrillo (USFWS-Red Bluff biologist). Field visits to the Red Bluff Diversion Dam, Battle Creek, and Clear Creek screw trap sites. PSMFC also examined databases provided by Cramer Fish Sciences and the USFWS Red Bluff office. These databases contained RST data collected on the Stanislaus River, Battle Creek, and Clear Creek. Recent Battle Creek and Clear Creek annual reports were examined to determine data analysis routines used by USFWS Red Bluff office. Analysis routines used by the USFWS Red Bluff office for RSTs located at the Red Bluff Diversion Dam were demonstrated by Felipe Carrillo.

In addition to corresponding with most of the people listed above, personnel at WEST Inc. reviewed the following documents relating to RST data and estimation techniques:

- Battle Creek RST report for Oct 2005 - Sep 2006;
- Red Bluff Diversion Dam RST reports for 2005 and 2006;
- Clear Creek RST report for Oct 2006 - Sep 2007;
- Mill and Deer Creek RST report for 1999;
- Butte and Big Chico Creek RST report for 2006-2007;
- Knights Landing RST report for Sep 1999 through Sep 2000;
- Feather River RST report for 2002 – 2004;
- Yuba River RST report for 2004 – 2005;
- Lower American RST River report for Oct 1998 – Sep 1999;
- Lower Mokelumne River RST report for Dec 2005 – Jul 2006;
- Lower Stanislaus River RST reports for 1999 and 2008;
- Lower Tuolumne River RST report for 2003;
- Lower Merced River RST report for 2008;
- the quantitative Appendix of the 2000 Red Bluff Diversion Dam RST report by Martin;
- “Determination of Salmonid Smolt Yield with Rotary-Screw Traps in the Situk River, Alaska, to Predict Effects of Glacial Flooding” by Thedinga et al (1994, *North American Journal of Fisheries Management,* p. 837-851);
- the 2000 review of Red Bluff Diversion Dam and Stanislaus River RST methods conducted by L. McDonald and S. Howlin;
- the 2000 review of Red Bluff Diversion Dam and Stanislaus River RST methods conducted by J. Skalski;
- response of D. Neeley to comments made by McDonald, Howlin, and Skalski during their review of the Red Bluff Diversion Dam and Stanislaus River RST methods; and
- the “Rotary Screw Traps and Inclined Plane Screen Traps” chapter of the American Fisheries Society protocol manual.

WEST Inc also reviewed the following databases provided by PSMFC:

- Cramer Fish Sciences databases containing RST data collected at Caswell State Park and Oakdale trapping sites on the Stanislaus River, and Hatfield State Park on the Merced River; and
- USFWS databases containing RST data collected from the Lower Clear Creek, Upper Clear Creek, and Upper Battle Creek RST's.

Minimum Field Data

The list of variables in this sub-section represents a minimum set of field measurements to be collected at each site. From these data, other quantities (such as catch, efficiency, % water fished, etc.) can to be estimated and in turn used to estimate abundance. Additional field data pertinent to a site may be collected. Additional field data may be collected if they are useful for purposes other than abundance estimation, or if they pertain to a unique feature of the site and can explain variation in daily catch or trap efficiency. Additional data that might be pertinent to a site include staff gauge readings of water depth, stream width, fish weight, etc.

Field data are of three basic types: (1) trap placement data, (2) trap check data, and (3) efficiency trial data. Within trap check data, four classes of data exist: (a) trap operating characteristics, (b) physical environment measures, (c) fish counts (1 value per trap check), and (d) individual fish measures (multiple values per trap check). The minimum set of variables to be measured for each type of data is listed below.

Trap Placement Data

Any time a trap is turned on (e.g., after installation or after movement) or turned off (e.g., prior to removal or prior to movement), the following data should be recorded:

1. Trap ID
   Description: Manufacture's serial number or other unique code associated with the trap. This number should be used to identify the trap for the trap's entire lifetime. This number should not be changed or re-assigned to another trap;
2. Site code
   Description: Unique ID of the overall stream location, e.g., stream name and river mile. If trap was installed or turned on, this is the code for the trap's location after Date and Time (below). If the trap was pulled or turned off, this is the code for the trap's location prior to Date and Time;
3. Fishing location
   Description: Unique ID of fishing location *within* the site. For example, '01', '02', or '03' if there are 3 fishing locations at a site. If there is only one fishing location at the site, this number assigned should be '01';
4. Date
   Description: Date of the change in trap status. Date that the trap began fishing, or date that trap stopped fishing;

5. Time

    Description: Time of the change in trap status. Time trap began fishing, or time trap stopped fishing; and

6. Fishing?

    Description: A binary Yes/No variable. Yes = trap was fishing after the above Date and Time, No = trap was not fishing after the above Date and Time.

Every trap must have a [*site, fishing location, date, time*] quadruplet corresponding to when it began fishing, and a [*site, fishing location, date, time*] quadruplet when it stopped fishing, unless the trap remains fishing on the current date. *Trap ID* can be used to lookup cone diameter, max cone depth, and other characteristics of the trap. S*ite* can be used to lookup characteristics of the overall installation, such as river mile, latitude, longitude, etc. *Site* and *Fishing location* can be used to lookup characteristics of the trap's specific locations, such as channel location (thalweg, right bank, left bank, etc), bottom type, etc.

Trap Check Data

A trap check occurs when a RST is visited and captured fish are processed. The exact schedule of trap checks is left to the biologists in charge of each program, and can vary from RST to RST. Ideally, traps will be checked every day during the season when the species of interest is expected to be in the river. When traps are not checked on a day, data for that day will be treated as missing (see imputation method described in Abundance Estimation Methods).

At a minimum, the following data should be collected every time a trap is checked:

1. Trap operating characteristics:
    a. Site code (to match site code in Trap Placement data, e.g., stream name and river mile);
    b. Fishing location (to match fishing location in Trap Placement data);
    c. Date (of trap check);
    d. Time (of trap check);
    e. Cone rotation counter reading;
    f. Cone rotation speed (rpm);
    g. Submerged cone depth (meters, measured from water surface to lowest part of submerged cone or read from gauge on trap); and
    h. Trap retention rate (intra-trap catch rate, depends on baffle configuration, usually 50% or 100%).
2. Physical environment variables:
    a. Water velocity (m/s, near trap, preferably near front of cone);
    b. Water temperature (°C, in front of cone at depth);
    c. Debris occlusion (%, visual);
    d. Turbidity (at least Secci depth);
    e. Average flow between last check and current check (cubic meters per second, measured at most representative river gauge); and
    f. River gauge ID (Identifier of river gauge used to calculate the above average flow).

3. Fish counts:
    a. Total number of unmarked fish caught (count or estimate);
    b. Estimate? (Yes/No, Yes = number of unmarked fish is an estimate, No = number of unmarked fish is a complete count);
    c. Total number of marked fish caught; and
    d. Total number of measured unmarked fish (number in subsample, if subsample was taken).
4. Individual fish data:
    a. For marked fish:
        i. Mark description code (e.g., AF-CL-BB = adipose fin – clipped – stained Bismarck brown, must be sufficient to identify the release group);
        ii. Fork length; and
        iii. Species.
    b. For measured unmarked fish:
        i. Fork length;
        ii. Species; and
        iii. Visual smolt index (0,1,2,3,4,5).

It is assumed that the trap has been fishing between date and time of the previous check until date and time of the current check. Cone rotations between previous check and current check, times rotation speed, will be used to compute amount of water sampled.

Efficiency Trial Data

Efficiency trials consist of releasing a known number of (uniquely or batch) marked fish upstream of a RST. By noting the number of marked fish from each release that were later captured in the RST, efficiency (probability of capture) can be estimated. Like trap checks, the exact schedule efficiency trials is left to the biologist in charge of each program. Ideally, it will be possible to release small batches of marked fish every day so that efficiency trials occur continuously throughout the season. However, large numbers of efficiency trials are not possible at many RSTs. In these cases, two to three efficiency trials per week are recommended. Less frequent efficiency trials are acceptable because probability of capture will be modeled after the season (see Abundance Estimation Methods below).

For every efficiency trial, the following should be recorded:
1. Date (of efficiency trial release);
2. Time (of efficiency trial release);
3. Dark? (Yes/No, Was sun down during release?);
4. Release location code (e.g., stream name and river mile);
5. Location of release in channel (e.g., LB, CC, RB, etc. for left bank, center current, right bank, etc.);
6. Nearest downstream RST site code;
7. Distance from release location to nearest RST (river km);
8. Mark description code (to match fish data above);
9. Number of marked fish released;
10. Holding time (hours);
11. Fish source (wild, hatchery, etc.);

12. Species;
13. Number of fish measured; and
14. Fork length for every measured fish.

Abundance Estimation Methods

This section contains recommendations for statistical estimation of abundance from data collected by RSTs in the Central Valley. These estimation techniques are designed to utilize the minimum set of field data (previous section) and are intended to be applicable to all RST sites that collect this data. The recommended analysis is widely applicable because it applies to all sites that collect the minimum set of field data. The recommended analysis is stable in the sense that, when appropriate, sites and years can be combined to improve model estimation. Such combination of data would likely require judicious use of covariates (such as 'site' and 'year' variables), but can be done in some cases.

The analysis leaves open the exact protocol by which researchers measure variables contained in the minimum set of data. Ideally, each site can provide unbiased and precise (low variance) estimates of the basic variables listed in the previous section. This means, ideally, that each site could provide unbiased estimates of counts, velocity, cone depth, rotations, etc. If estimates of the basic variables are unbiased, the abundance estimates produced using methods in this section should also be unbiased. If unbiased estimates of the minimum dataset cannot be constructed, at least consistently measured estimates should be used. Readings from a poorly calibrated velocity or temperature meter is an example of a consistently measured, yet biased estimate. Consistently measured basic variables, when used in abundance estimation, will result in an index of juvenile abundance at the site that can at least be assessed for trends.

As called for in the cooperative agreement between CAMP and PSMFC, the methodological recommendations contained in this section were designed to estimate abundance of all life stages and runs of juvenile Chinook salmon. However, the methods outlined here are not specific to life stages or runs of a single species. The methods are applicable to all species, life stages, and runs provided similar and adequate data on these populations can be collected. The only caveat to wide-spread application of these methods is that the estimator's performance, while theoretically sound, may not perform well when samples sizes are low. A prudent amount of faith should be placed in abundance estimates produced by these methods for species other than Chinook.

General Estimation Approach

In his review of methods at Caswell State Park on the Stanislaus River, Skalski (2000) mentioned the virtues of a *design-based* estimation approach, and the vices of a *model-based* estimation approach. The general definition of a design-based approach is that the analysis relies on a few simple assumptions about the structure of the data and uses replication of measurements or samples as the basis for assessing variation. For example, if RST catch and trap efficiency could be assessed every day without error, a design-based approach would estimate abundance that day as catch divided by efficiency. Variation in abundance across days would be used to construct confidence intervals. Design-based approaches typically involve relatively simple estimators, like means, ratios, and products. On the other hand, model-based approaches make relatively weighty assumptions about the data structure, or what influences a particular variable, and uses these assumptions as the basis by which they assess variation. For example, a model-based approach could assume that the mean of a response variable follows a regression relationship, and that errors in the regression relationship follow a normal distribution. Model-based estimators can become quite complicated depending on the complexity of the situation and assumed model.

The virtues of a design-based approach include its simplicity and lack of assumptions (Skalski, 2000). It is hard to argue against properly designed and executed design-based estimates (Olsen and Smith, 1999). However, the two biggest vices of a design-based approach are its inability to include measurement error and a high data requirement that is generally required. Design-based approaches also have difficulty incorporating missing values into the analysis. The virtues of a model-based approach include its ability to incorporate measurement error, lower data requirements, and the ability to make estimates outside the data range (extrapolation) when necessary. However, the main vice of a model-based approach is the fact that its assumptions will always be violated to some extent and thus estimates are easy to question. Model-based approaches can use outputs of a model as substitutes for field data, thereby giving researchers the feeling that results are "far from" or "insulated from" the original data.

The abundance estimation procedure described here is neither fully design-based nor fully model-based. The approach advocated here uses raw data when it is appropriate, but assumes a flexible non-linear model for catches and efficiencies when raw counts or efficiencies do not apply to an entire interval between checks. The non-linear model allows estimation of daily abundance during times when the trap was not operating or when an efficiency trial has not been done for quite some time. In utilizing a model, the data collection requirements are reduced relative to a fully design-based approach because fewer checks and efficiency trials can be performed once the model is established and stable. If the models continue to be developed over time, accuracy and precision will increase through time. Utilizing a model for certain tasks also smoothes a portion of the random noise inherent in measurements, thus making estimate more stable.

The approach advocated here uses raw catch data when it is available, and model based estimates when raw catch is not available. On days when a RST check meets protocol, raw counts are inflated by a current estimate of trap efficiency without aid of a model for catch. A trap check 'meets protocol' if the interval between checks was 24 ± 2 hours (or, some other interval surrounding 24; in the remainder, 2 hours will be assumed) and the trap was in operation for that entire period. When counts are not available for a day (check does not 'meet protocol'), the approach employs a generalized additive model (GAM) (Hastie and Tibshirani, 1990) to estimate catch as a function of study covariates. To estimate trap efficiencies, the approach uses a second GAM estimated from past and current efficiency trials. Both of these GAMs can be functions of time (date of season) and other factors such as flow, percent flow sampled, turbidity, distance from trap to release site, etc.

Several RST operations in the Central Valley already employ models to infer various quantities when they are missing. For example, a 5-day moving average with a triangular weight function is used on data collected at Caswell State park to estimate catch on days when it is missing. Moving averages are special cases of a GAM model. Another model typically employed by RST operations is to assume trap efficiency remains constant between efficiency trials. On days when an efficiency trial has not been conducted, researchers typically use efficiency from the last trial to inflate raw counts.

Abundance Estimation

The basic quantities contained in this sub-section are estimable from the minimum set of field data collected at a site. At most sites, these quantities can be estimated from historical data and thus past estimates could be re-computed or updated using this methodology if necessary. In other cases, these estimates cannot be computed from historical data. At those sites, data collection procedures will need to change if these procedures are to be applied in the future.

The two basic quantities needed to estimate abundance at every site are:

- $\hat{c}_{ij}$ = either the enumerated or estimated catch of unmarked fish of a certain life stage in trapping location i at the site during the 24 hour period indexed by j. For example, $\hat{c}_{23}$ = estimated catch at the 2nd trapping location during day 3; and
- $\hat{e}_{ij}$ = estimated trap efficiency at trapping location i of the site for a certain life stage during the 24 hour period indexed by j. For example, $\hat{e}_{23}$ = estimated efficiency at the 2nd trapping location during day 3.

Note that, for notational convenience, a subscript for site is not present in the above quantities. It is assumed that estimates will be computed separately for each site, thus eliminating the need for a site subscript.

Assuming the above quantities can be computed, an estimate of the number of fish passing the trap during the 24-hour period indexed by j is:

$$\hat{N}_{ij} = \frac{\hat{c}_{ij}}{\hat{e}_{ij}} \quad (1)$$

Estimation of $\hat{c}_{ij}$

The estimate of catch, $\hat{c}_{ij}$, will be computed in one of three ways. First, if the interval between check j and check $j - 1$was 24 ± 2 hours and the trap operated properly for the entire period, $\hat{c}_{ij}$ will be the total catch of unmarked fish in the trap at check j. Note that the amount of time the trap operated properly is estimated as the difference in rotation counter readings multiplied by cone rotation speed averaged over the two checks. When the check meets protocol, $\hat{c}_{ij}$ can either be a complete enumeration of captured fish, or an estimate based on random subsampling when too many fish are captured to enumerate.

The second method of computing $\hat{c}_{ij}$ will be used when the trap fishes for less than 22 hours. If the trap fished for less than 22 hours between check j and check $j-1$, the fish count at time j will be adjusted using a diurnal logistic regression model. This diurnal logistic regression model will utilize efficiency trial data to estimate the proportion of a typical 24-hour fish count passing in a given period of time. To estimate this logistic regression, data from many efficiency trials and multiple checks will be used. Assuming m_i is the number of marked fish captured within 24 hours of release during the i^{th} efficiency trial, the logistic regression will estimate the proportion of m_i captured within t hours ($t < 22$) of release as a function of other covariates like day-night, flow, date, etc. To do this, the trap check time of the m_i marked fish must be known, and the interval between release and check must vary from 0 to 24 over multiple efficiency trials. When a trap is checked t hours ($t < 22$) after the previous check, $\hat{c}_{ij}$ will be computed as:

$$\hat{c}_{ij} = \frac{c(t)}{p(t)}$$

where $c(t)$ is the catch of unmarked fish in the t hours since the last check and $p(t)$ is the estimated (via logistic regression) proportion of a typical 24-hour catch caught within t hours under similar conditions. Until sufficient data is available to adequately estimate the logistic regression model, $\hat{c}_{ij}$ will be treated as missing when a full 24 hours has not been sampled. In this case, $\hat{c}_{ij}$ will be estimated using the GAM (below).

The third method of computing $\hat{c}_{ij}$ will be employed when $\hat{c}_{ij}$ is missing for some reason (i.e., trap fished for >26 hours between checks). In this case, $\hat{c}_{ij}$ will be predicted after the season using a Poisson GAM model fitted to the $\hat{c}_{ij}$ that met protocol. The additive portion of this model will be of the general form:

$$log(E[c_{ij}]) = s(j) + \beta_1 x_{ij1} + \cdots + \beta_p x_{ijp} \quad (2)$$

where $s(j)$ is a smooth (spline) function of the day index (i.e., smooth function of Julian date), the x_{ijk} are covariates associated with trap i during day j, and the β's are estimated coefficients. In other words, the GAM has a non-linear smoothing component, $s(j)$, as well as a linear component, symbolized by the $\beta_k x_{ijk}$. The smoothing component requires choice of the degree of smoothing that the function should do. Automatic and objective choice of the smoothing amount should be done by generalized cross-validation, or similar established technique.

Estimation of $\hat{e}_{ij}$

Efficiency estimates at the *i-th* trapping location on day j will be computed from a binomial GAM, unless sufficient efficiency trials (≥3 per week) have been performed. If sufficient efficiency trials have been conducted, and the assumption of constant efficiency between trials is justified, efficiency from the most recent trial will be used for $\hat{e}_{ij}$. When the most recent efficiency is not appropriate, a binomial GAM fitted to past and current efficiency trials will be estimated and used to compute $\hat{e}_{ij}$. The additive portion of this GAM model will be of the form:

$$log\left(\frac{E[\hat{e}_{ij}]}{1-[E[\hat{e}]_{ij}]}\right) = s(j) + \gamma_1 z_{ij1} + \cdots + \gamma_p z_{ijp} \tag{3}$$

where $s(j)$ is again a smooth (spline) function of the day index (i.e., smooth function of Julian date), the z_{ijk} are covariates associated with the efficiency of trap i during day j, and the γ's are estimated coefficients. Again, automatic choice of the smoothing amount should be by generalized cross-validation, or similar established technique.

The current abundance estimation methods employed at Red Bluff Diversion Dam utilize a linear regression model containing the proportion of flow sampled between checks (i.e., %Q) to estimate trap efficiencies. The linear model used at Red Bluff Diversion Dam is a special case of the GAM proposed here (i.e., no $s(j)$ and only one z). The GAM proposed here allows for non-linear smoothing and inclusion of additional factors that may influence efficiency. For example, %Q, turbidity, and distance from release site could all be incorporated in the linear or non-linear parts of the model. Note that the absolute accuracy of covariates in the model (e.g., flow, %Q, etc.) is not paramount. It is only paramount that covariates in the model be consistently and objectively measured. Because the GAM model is invariant to linear transformations of the covariates, a proxy for any covariate can be used provided it is a linear transformation of the desired covariate.

Estimation of $\hat{N}_{ij}$

Once $\hat{c}_{ij}$ and $\hat{e}_{ij}$ are estimated, and $\hat{N}_{ij}$ has been computed, abundance estimates for the site should be computed by summing over trap locations. The total number of fish passing a particular site on day j should be computed as:

$$\hat{N}_j = \sum_{i=1}^{n_{ij}} \hat{N}_{ij}$$

where n_{ij} is the number of trapping locations fishing at site i during day j. Abundance on day j can then be summarized in a number of ways. The estimates $\hat{N}_j$ can be plotted against j to visually assess trends. $\hat{N}_j$ can be summed over a week, month, or year to produce weekly, monthly, or annual estimates of abundance. The time series of $\hat{N}_j$ estimates can be subjected to further analysis to detect and quantify trends.

Confidence Interval Estimates

The abundance estimator $\hat{N}_j$ is a mixture of measured and modeled fish counts, as well as modeled trap efficiency values. This mixture makes variance computation by traditional methods difficult because they rely on formulas and approximations. Here, confidence intervals for $\hat{N}_j$ will be computed by parametric bootstrap or Monte Carlo methods. This method has been successfully used at Battle and Clear Creek to compute confidence intervals for their abundance estimates.

Fish counts derived from trap checks are subject to measurement error. For instance, it is possible for technicians to miss-count fish, miss-classify species, or miss-classify life history stage. However, the measurement error inherent in raw counts is tiny compared to the day-to-day and seasonal fluctuation in fish passage. Day-to-day and seasonal fluctuation in fish passage is natural process variation, sometimes called sampling variation to distinguish it from measurement error. Because measurement error in $\hat{c}_{ij}$ is tiny compared to other sources of error, raw counts will be treated as known constants. Similarly, the measurement error in raw efficiency estimates is tiny compared to process variation.

Modeled values of $\hat{c}_{ij}$ and $\hat{e}_{ij}$ are not constants, and variation of these predicted values from their respective GAMs will be included by the parametric bootstrap procedure described below. Values of $\hat{c}_{ij}$ that have been corrected for less than 24-hour fishing periods are not constants; however, it is assumed that there are relatively few of these values and that it will take some time before sufficient data exists to estimate the logistic regression. If the logistic regression has been estimated, and numerous $\hat{c}_{ij}$ have been corrected for less than 24-hour fishing periods, the coefficients of the logistic regression should be included in the parametric bootstrap method outlined below. In this case, coefficients of the logistic regression would be treated the same as coefficients from the Poisson or binomial GAM.

Coefficients in both the Poisson GAM and binomial GAM are maximum likelihood estimates. A mathematical fact about maximum likelihood estimators is that their distribution converges to a multivariate normal distribution as sample size increases. Let $\hat{\boldsymbol{\beta}}$ represent the vector of smoothing and linear coefficients in the Poisson GAM model for missing fish counts, and let $\hat{\boldsymbol{\gamma}}$ represent the vector of smoothing and linear coefficients in the binomial GAM for trap efficiency. The parametric bootstrap procedure assumes both of these vectors are approximately multivariate normal random vectors, i.e.,

$$\hat{\boldsymbol{\beta}} \sim MVN\left(\boldsymbol{\beta}, \hat{V}\left(\hat{\boldsymbol{\beta}}\right)\right)$$
$$\hat{\boldsymbol{\gamma}} \sim MVN\left(\boldsymbol{\gamma}, \hat{V}(\hat{\boldsymbol{\gamma}})\right)$$

where *MVN* stands for the multivariate normal density function, and $\hat{V}\left(\hat{\boldsymbol{\beta}}\right)$ and $\hat{V}(\hat{\boldsymbol{\gamma}})$ are estimated variance-covariance matrices from the GAM model. $\hat{V}\left(\hat{\boldsymbol{\beta}}\right)$ and $\hat{V}(\hat{\boldsymbol{\gamma}})$ will be estimated using the 2nd derivative of the likelihood, or the observed Fisher information matrix.

Given these assumptions, the parametric bootstrap procedure proceeds as follows:

1. Generate realizations from the multivariate normal distribution. Specifically, generate the random vector $\hat{\boldsymbol{\beta}}^*$ from a $MVN(\hat{\boldsymbol{\beta}}, \hat{V}(\hat{\boldsymbol{\beta}}))$ distribution, and the random vector $\hat{\boldsymbol{\gamma}}^*$ from a $MVN(\hat{\boldsymbol{\gamma}}, \hat{V}(\hat{\boldsymbol{\gamma}}))$ distribution. If a logistic regression equation is in use to correct for less

than 24-hours of fishing between checks, a random *MVN* vector representing its coefficients should also be generated.

2. Evaluate the Poisson GAM model in Equation (2) using $\hat{\boldsymbol{\beta}}^*$ for all days with missing fish counts. This will result in the random realizations $[E[\hat{c}]_{ij}]^*$ for all days with missing fish counts.
3. Evaluate the binomial GAM model in Equation (3) using $\hat{\boldsymbol{\gamma}}^*$ for all days. This will result in the random realizations $[E[\hat{e}]_{ij}]^*$ for all days.
4. For all days with missing fish counts, generate random Poisson variables $\hat{c}_{ij}^*$ from *Poisson*($[E[\hat{c}]_{ij}]^*$) distributions.
5. For all days, generate random binomial proportions $\hat{e}_{ij}^*$ from *binomial*($[E[\hat{e}]_{ij}]^*, \bar{r}_j$) distributions, where $\bar{r}_j$ is the (rounded) average number of released fish in the two efficiency trials on either side of day *j* temporally.
6. Recalculate $\hat{N}_{ij}$ for all days via Equation (1), substituting randomly generated values where appropriate. Specifically, use observed values of $\hat{c}_{ij}$ on days when counts are present, and substitute $\hat{c}_{ij}^*$ for $\hat{c}_{ij}$ on days when counts are missing. Substitute $\hat{e}_{ij}^*$ for $\hat{e}_{ij}$ on days when efficiency has been estimated from the binomial model. This results in a random series of abundance estimates for trap *i* of a particular site. Label these random estimates $\hat{N}_{ij}^*$.
7. Recalculate abundance for the site (i.e., $\hat{N}_j$) using the $\hat{N}_{ij}^*$. This results in a random time series of $\hat{N}_j^*$ values (for all *j*). Summarize these $\hat{N}_j^*$ values the same way they were summarized to compute the original estimates (i.e., sum over weeks, months, years, etc.).
8. Store the time series of $\hat{N}_j^*$ values and any derived summarizations.
9. Repeat the above steps 5000 times. This results in 5000 random realizations of $\hat{N}_j^*$ and subsequent summaries.
10. Finally, construct 90% confidence intervals as the 5th and 95th percentiles of the appropriate set of 5000 random abundance values. Specifically, the 90% confidence interval for $\hat{N}_j$ extends from the 5th percentile to the 95th percentile of the distribution of 5000 $\hat{N}_j^*$. Similarly for the confidence intervals on subsequent summarizations of $\hat{N}_j$. Error bands for visual displays of $\hat{N}_j$ can be computed by connecting the 5th and 95th percentile values in a graph of $\hat{N}_j$ through time.

A virtue of this parametric bootstrap technique is that it relies on only three parametric assumptions, and does not approximate any variances of derived estimators. The parametric assumptions this procedure makes are (1) missing fish counts follow a Poisson distribution, (2) efficiency values follow a binomial distribution, and (3) coefficients in both GAMs follow a multivariate normal distribution. A vice of this technique is that because it does not involve a mathematical formula, it must be computed using a conceptually simple but complex computer program. Note also that in order to carry out the computation, all covariate values must be available to evaluate the GAM models.

Trend Detection

There are two types of trend that can be detected from the time series of abundance estimates outlined above. The first type of trend is *abrupt change* that happens in a very short period of time (e.g., 1 or 2 years). The second type of trend is *long-term steady changes* in abundance that tend to move the mean in a single direction. Due to the high variability inherit in most juvenile production estimates, abrupt change is difficult to detect. Analyses to detect abrupt change can be run, but they will not be discussed here. It is assumed that long-term steady changes are of interest and an analysis designed to detect such trends will be discussed below. It should be kept in mind that the number of analyses that could be used to detect "trend" of some kind is large. The best analysis to detect trend is often a function of the specific objectives of the analysis and particulars of the data set being analyzed. In this section, a generic trend detection analysis (regression over time) will be described. It is hoped that this analysis will be applicable to a wide range of situations.

Detection of long-term trends can be divided into 2 inference scenarios. One inference scenario utilizes data from a single site and makes inference to parameters specific to that site. The other inference scenario assumes data from multiple sites within a region will be pooled to make inference about a parameter defined on the region. These latter inferences are called region-wide. Because multi-site region-wide trend detection analyses are generally extensions of single-site trend detection analyses, and because it is anticipated that single-site trend analyses will be more common, only single-site analyses will be discussed here. A qualified statistician should be consulted when multi-site trend detection analyses are to be performed.

It is assumed that trends in annual juvenile production are of interest. This assumption implies that total annual production will be the primary response of interest. It is assumed that an estimate of the standard error of annual production is available (see Confidence Interval Estimation above).

Long-term trends are estimated and detected using a mixed or fixed effect linear model and testing for the presence of non-zero slope coefficients. In matrix notation, a simple fixed effect model with no covariates (other than time) will be of the form:

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{E}$$

where **Y** is the vector of annual production estimates,

$$\mathbf{X} = \begin{bmatrix} 1 & year_1 \\ 1 & year_2 \\ 1 & year_3 \\ \vdots & \vdots \\ 1 & year_n \end{bmatrix},$$

and

$$\boldsymbol{\beta} = \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix},$$

is a vector unknown coefficients to be estimated, and **E** is a vector of unknown random errors. The $year_i$ values in **X** are the actual years for each production estimate (e.g., 2006, 2007, 2010, etc.). If production was not estimated in a particular year, that year would not appear in **X**. Consequently, n is the number of data points, not the number of years that the overall monitoring program has been collecting data.

The above model assumes that the long-term trend at a site is linear, but linearity is not necessary. Linearity of trend is not necessary because curvilinear or polynomial trends can be fitted and their coefficients tested for equality with zero. If auxiliary variables, such as mean temperature, flow, ocean conditions, etc. are correlated with annual production, these covariates can be incorporated into the model to explain variation and improve precision. If additional covariates are included, additional columns would be appended to **X**.

If production estimates are approximately normally distributed and residuals of the model are uncorrelated, standard least squares methods can be used to estimate and test whether the slope parameter in $\boldsymbol{\beta}$ is non-zero. If the slope is significantly different than zero, significant trend has been detected. If production estimates are not approximately normal, but residuals are uncorrelated, generalized linear model (GLM) estimation routines can be used to estimate and test whether the slope is zero. If production estimates are approximately normal, and residuals are correlated through time or space, mixed effect linear model estimation techniques can be used to estimate $\boldsymbol{\beta}$ and test for trend. Finally, if production estimates are not approximately normal, and residuals are correlated through time or space, generalized mixed linear model estimation techniques can be used. Alternatively, bootstrap methods can be used to test $\beta_1 = 0$ in the uncorrelated case, and block bootstrap methods (Lahiri, 2003) can be used in the correlated case. Bayesian analyses for each of the above cases are also available (consult a qualified statistician).

Conclusions

A unified data analysis procedure is feasible for the RST program in the Central Valley of California. Most RST sites are already collecting the minimum set of data required to carry out the estimation procedure set forth above. The database, while complex, need only house the minimum set of variables to be useful for estimating abundance. The estimation procedure is flexible enough to allow missing counts, varying trap check intervals, variable efficiency trial schedules, and variable numbers of efficiency trials across sites.

If absolutely necessary, estimates of fish passage can be made during times of high flow by extrapolating the GAM models if the appropriate covariates are collected and if it can be assumed that the basic form of the model holds during high flows. If this assumption does not hold, estimates of fish passage during high flows cannot be made. As the GAM models are refined over time with more and more data, predictions should become more and more accurate and precise. For instance, it is not too much to hope that one day a RST will continue fishing during high flows. By using this information, however scant, to help estimate coefficients of the GAMs, researchers may one day be comfortable with abundance estimates during high flows.

Literature Cited

Hastie, T.J. and Tibshirani, R.J (1990) *Generalized Additive Models,* London: Chapman and Hall.

Lahiri, S. N. (2003) *Resampling methods for dependent data*. New York: Springer.

Olsen, A.R. and Smith, E.P. (1999) "Introduction to the Special Issue on Surveys Over Time", *Journal of Agricultural, Biological, and Environmental Statistics,* **4**(4), 328-330.

Skalski, J. (2000) "Technical Review of Demko et al. (2000): Outmigrant Trapping of Juvenile Salmonids in the Lower Stanislaus River, Caswell State Park Site, 1998" Report prepared for Scott Spaulding, USFWS Sacramento-San Joaquin Estuary Fishery Resource Office, Stockton, CA.